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A Relative Study of Bilateraland Propagated Image Filtering On Various Noisy Pixels

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ABSTRACT:
Filtering is most fundamental operation of image processing and computer vision. The term filtering focus on the value of the filtered image at a given location. Filtering typically requires the extraction of particular image characteristics, while undesirable patterns like noise (or) irrelevant textural regions need to be disregarded. If cross-region mixing occurs during filtering process, the output image would contain blurry regions which result in discarded visual quality .This paper discuss about propagated image filtering approach as a novel image filter with the goal of smoothening over neighbouring image pixels while preserving image context like edges or textural regions. The proposed method is effective at removing signal noise while enhancing the experimental results in perceptual quality. We will show that improved performance over existing bilateralimage filters.

INDEX TERMS—*Bilateral filter, de-blurring, noise removal, range filter, sharpness.*

I. INTRODUCTION

A digital image (also called a discrete image) comes from a continuous world. It is obtained from an analogue image by sampling and quantization. This process depends on the acquisition device and depends, for instance, on CCDs for digital cameras. Basically, the idea is to superimpose a regular grid on an analogue image and to assign a digital number to each square of the grid, for example the average brightness in that square. Each square is called a pixel, for picture element, and its value is the gray-level or brightness.

In image processing, a filter is a device or process that removes some unwanted components or features from a signal.The defining feature of filters being the complete or partial suppression of some aspect of the signal. There are many different bases of classifying filters and these overlap in many different ways.

Filters may be: linear or non-linear,time-invariant or time-variant, also known as shift invariance. If the filter operates in a spatial domain then the characterization is space invariance. Image restoration refers to the genre of techniques that aim to recover a high quality original image from a degraded version of that image given a specific model for degradation process. Thus restoration techniques are oriented towards modelling the degradation and applying the inverse process in order to recover the original image.

A bilateral filter is a non-linear, edge-preserving and noise-reducing smoothing filter for images. The intensity value at each pixel in an image is replaced by a weighted average of intensity values from nearby pixels. This weight can be based on a Gaussian distribution.

The guided filter is also a more generic concept beyond smoothing: it can transfer the structures of the guidance image to the filtering output, enabling newfiltering applications.

Bilateral and guided filters are popular edge-preserving image filters, which are able to alleviate the aforementioned problem during the filtering process.

The idea of these filters is to observe and process neighbouring pixels with similar pixel values, so that desirable image context can be preserved. Both bilateral and guided filters have been successfully applied to a variety of applications such as noise reduction, tone management, and image fusion. However, these filters require predefined pixel neighbourhood regions (via spatial functions or kernels), which are typically difficult to determine beforehand.

Propagation filter is able to observe and preserve image characteristics without the need to apply explicit spatial kernel functions. This filtering process can be regarded as a one-step estimator, which minimizes the expected error between the filtered and desirable image outputs. In the experiments, several image processing

applications such as image de-noising/smoothing, image fusion, and high-dynamic-range (HDR) imaging will be considered.

II. LITERATURE SURVEY

A. Gaussian Filter

To introduce bilateral filtering, we first describe the Gaussian convolution. This filter is close to the bilateral filter but is not edge-preserving. We will use it to introduce the notion of local average to underscore the specificities of the bilateral filter that make it edge-preserving.

Linear Filtering with Gaussian Blur (GB) Convolution by a positive kernel is the basic operation in linear image filtering. It amounts to estimate at each position a local average of intensities and corresponds to low-pass filtering .One defines the Gaussian blur (GB) filtered image by:

GB[I] p = q∈SGσ(||p − q||) Iq,.... (1)

whereGσ(x) denotes the two-dimensional Gaussian kernel

Gσ(x) = 1 2π σ2 exp − x2 2 σ2.... (2)

So, Gaussian filtering is a weighted average of the intensity of the adjacent positions with a weight decreasing with the spatial distance to the centre position p. This distance is defined by Gσ(||p − q||), where σ is a parameter defining the extension of the neighbourhood.

B. Bilateral Filter

Nonlinear Filtering with Bilateral Filter Similarly to the Gaussian convolution, the bilateral filter is also defined as a weighted average of pixels. The difference is that the bilateral filter takes into account the variation of intensities to preserve edges. The rationale of bilateral filtering is that two pixels are close to each other not only if they occupy nearby spatial locations but also if they have some similarity in the photometric range.

C. Propagation filter

Propagation filter is able to observe and preserve image characteristics without the need to apply explicit spatial kernel functions

III. PROBLEM STATEMENT

The main goal in this work is to improve the performance of image filtering by reducing noise. However all of these have various issues (such as expensive equipment, low visual quality and performance).In this paper ,will look at how we can improve image characteristics without the need to apply explicit spatial kernel functions, both with regards to performance and visual quality.We will show that our filtering process essentially operates the merits of bilateral and geodesic filtering and can be regarded as a robust estimator, which minimizes the expected error between the filtered and desirable image outputs.

IV. PROPOSED SYSTEM

Propagation filter utilizes the idea that the relationships between pixels can be observed and propagated along a path in an image. And, for any two pixels to be related, all the intermediate pixels along the path should be related as well. We determine pixel relationships based on photometric distances between pixels. Instead of using predefined spatial kernel as bilateral and guided filters do (or completely relying on photometric relationship as geodesic filters do), propagation filter directly determines pixel relationships based on spatial and photometric information in the images. We achieve this by differentiating photometric relationships between the two adjacent pixels and two remote ones, and we formulate such relationships in a probabilistic fashion via Baye's rules. This algorithm can efficiently prevent information crossing image edges and further alleviate cross-region mixing problems. We will show that our propagation filter essentially cooperates the merits of bilateral and geodesic filtering, while comparable computation costs can be obtained.

V. IMPLEMENTATION

A. Bilateral Filter

Step 1: The bilateral filter splits the input image into two layers.

Step 2: A large-scale component which is a smoothed version of the input with the main contours preserved, and a small-scale component which is the residual of the filter.

Step 3: Depending on the settings and the application, this small-scale component can be interpreted as noise or texture.

Well known as an edge-preserving filter, the bilateral filter calculates the value for pixel s as follows:

$$I'_s = \frac{1}{Z_s} \sum_{t \in \Omega} g(d_{\mathrm{BF}}(s,t); \sigma_S)\, g(d_{\mathrm{BF}}(I_s, I_t); \sigma_r)\, I_t,$$

Where I $_0$ s is the filtered output at pixel s, Ω denotes the set of pixels t in the input I, and g(x; σ) is a Gaussian function with variance σ 2. For bilateral filters, the spatial and photometric distances between pixels s and t are defined as:

$$d_{\mathrm{BF}}(s,t) = \|t - s\|, \text{ and } d_{\mathrm{BF}}(I_s, I_t) = \|I_t - I_s\|,$$

Which calculate the Euclidean distance between their locations and that between their pixel values, respectively. Thus, bilateral filtering considers both spatial and photometric distances between pixel values, and applies the weighted pixel value as the filtered output.

$$d_{\mathrm{BF}}(I_s, I_t) = \sqrt{\sum_{x, x+1 \in \phi} \|I_{x+1} - I_x\|^2},$$

APPLICATIONS:

De-noising: This is of course the primary goal of bilateral filter, and it has been used in several applications such as medical images, movie restoration, etc

Texture and Illumination Separation, Tone Mapping, Retinex: small-scale decomposition of images, these applications edits texture and manipulates the tonal distribution of an image to match the capacities of a given display or achieve photographic stylization.

Three-dimensional Fairing: This is the counterpart of image de-noising for three-dimensional meshes and point clouds. Noise is removed from these data sets.

a. Propagation Filtering

Cross-region mixing is a typical problem for existing filters when performing image processing tasks like de-noising or smoothing. For example, although bilateral filters measure the photometric distances between pixels for determining the filter weights, their use of explicit spatial filtering kernels would inevitably assign weights to pixels across image regions.

Step 1: The One-Dimensional case Given an input image I, the filtered output I $_0$ s at pixel s produced by our propagation filter is calculated by

I $_0$ s = 1 Zs X t∈N (s) ws,t It

Whereit denotes the value at pixel t in I, and N (s) indicates the set of neighbouring pixels centered at s.

Step 2: We have ws,t as the weight for each pixel t to perform the filtering of Is, while Zs = P t∈N (s) ws,t as the normalization factor for ensuring the sum of all ws,t equal to 1.

Step 3: We first define that pixels y is photo metrically related to pixel x, or x r−→ y, if x and y have similar pixel values. In addition, if y is also adjacent to x, we say that y is adjacent photo metrically related to x, or x a−→ y.

Step 4:Given these two types of photometric relationships, we define the pixel relationship as follows:

Definition1. For pixel t being related to pixel s, the intermediate pixels between s and t not only need to be photo metrically related to s, they are also required to be adjacentphoto metrically related to their predecessors . As a result, we derive the filter weight ws,t by the following definition:

Definition2. Suppose there are n singly connected pixels, 1. . .n, and pixels s and t satisfying 1 ≤ s ≤ t ≤ n. The weight ws,t for filtering pixel s with pixel t is the probability value of t being related to s, i.e., P(s→t). If t = s, we have ws,s = P(s → s) = 1. As for t 6= s, based on Definitions 1 and 2, we calculate the weight ws,t by the Bayes' rule:

$$\begin{aligned} w_{s,t} &\equiv P(s \to t) = P\left(s \to t-1 \wedge t-1 \xrightarrow{a} t \wedge s \xrightarrow{r} t\right) \\ &= P(s \to t-1)\; P\left(t-1 \xrightarrow{a} t \wedge s \xrightarrow{r} t \mid s \to t-1\right) \\ &= w_{s,t-1}\; P\left(t-1 \xrightarrow{a} t \mid s \to t-1\right) P\left(s \xrightarrow{r} t \mid s \to t-1 \wedge t-1 \xrightarrow{a} t\right. \\ &\equiv w_{s,t-1}\; D(t-1,t)\; R(s,t)\,. \end{aligned}$$

The adjacent photometric relationship between pixels t and t−1. By assuming that the probability value of two adjacent pixels being photometric related is proportional to the value of a Gaussian function of their pixel value difference, we define

$$D(x,y) = g\left(\| I_x - I_y \|; \sigma_a\right) = \exp\left(\frac{-\| I_x - I_y \|^2}{2\sigma_a^2}\right)$$

Where Ix is the value of pixel x, and kIx −Iyk measures the Euclidean distance between the corresponding pixel value difference.
We have R(s, t) = P s r−→t|s→t−1 ∧ t−1 a−→t , which calculates the photometric relationship between pixels s and t. With s → t−1 and t−1 a−→ t, pixel t is viewed as adjacent to pixel s, and thus R(s, t) is measured as the adjacent-photometric relationship between s and t. As a result, we define

[redacted]

Based on the above definitions, we see that a large weight ws,t not only needs pixels s and t to have a strong photometric relationship (i.e., similar pixel values), it also needs large ws,t−1 and D(t−1, t) values for the intermediate pixels between s and t. That means, if any pixel along the path connecting pixels s and t is unrelated to either of them, t will be viewed as unrelated to s. In other words, a small ws,t will be resulted. This is the reason why our propagation filter is able to reflect image context information when performing filtering.

C.Propagation Filtering as a Robust Estimator

We now show that our proposed propagation filter can be viewed as a one-step estimator, which aims at minimizing the error between the filtered and desirable outputs (e.g., denoised or smoothed images). To start, we first transform our filtering algorithm of (6) into the following formulation:

$$I'_s = \frac{1}{Z_s} \sum_{t \in \mathcal{N}(s)} w_{s,t}\, I_t = I_s - \frac{1}{Z_s} \sum_{t \in \mathcal{N}(s)} w_{s,t}\,(I_s - I_t).$$

The above equation is effectively a gradient descent solver optimizing the objective function f, whose gradient at pixel s is derived as:

$$\nabla f = \sum_{t \in \mathcal{N}(s)} w_{s,t}\,(I_s - I_t).$$

With this gradient solver, the optimization problem can be recovered as:

$$\min_I \sum_{s \in \Omega} \sum_{t \in \mathcal{N}(s)} \int w_{s,t}\,(I_s - I_t)\; \mathrm{d}(I_s - I_t),$$

Where Ω denotes the pixel set of the input image.

D.Propagation Filtering as Belief Propagation

We now show that propagation filtering can be viewed as belief propagation with a Bayesian network. 2D path pattern for image filtering is a polytree (i.e., a directed acyclic graph). We now show that our filtering process is equivalent to the polytreealgorithm.

Let Xt as the random variable representing that pixel t is related to pixel s. A Bayesian network can be constructed using our proposed 2D pattern, which reflects the dependency between its nodes. By Definition 1, we have s and t−1 as the parent nodes of t, and t+1 as its child node.

Since there only exists a single directed path from t to t+1, the probability P(Xt) can be expressed as P(Xt) = P(Xs)P(Xt−1 | Xs)P(Xt | Xs∧Xt−1), where P(Xs) and P(Xt−1 |Xs) indicate the beliefs of Xs and Xt−1 . We now show that P(Xt) is effectively the weight ws,t as determined in our propagation filter. According to Definition 2, since pixel s is to be filtered, we have P(Xs) = ws,s = 1 and P(Xt−1 | Xs) = P(Xt−1) = ws,t−1 .

Based on the same definition, we calculate P(Xt | Xs, Xt−1) by P(t−1 a−→ t ∧ s r−→ t | s → t−1), and thus P(Xt) = ws,t−1P(t−1 a−→ t ∧ s r−→ t | s → t−1), which is the same as (7). From the derivations, we have P(Xt) = ws,t, which verifies that our propagation filtering can be regarded as the belief propagation polytree algorithm.

B. EXPERIMENTAL RESULTS

Propagation filtering process essentially co-operates the merits of bilateral and geodesic filtering and can be regarded as a robust estimator, which minimizes the expected error between the filtered and desirable image outputs.

B. CONCLUSION

We presented the propagation filter as a local filtering operator, which aims at smoothing over images while preserving image context information. Finally, a variety of applications computer vision and graphics verified the effectiveness of our propagation filter, which was shown to outperform existing image filters in terms of both quantitative and qualitative evaluations.

REFERENCES

[1] M. Aleksic, M. Smirnov, and S. Goma. Novel bilateral filter approach: Image noise reduction with sharpening. In Electronic Imaging, 2006.

[2] F. Durand and J. Dorsey.Fast bilateral filtering for the display of high-dynamic-range images.ACM Transactions on Graphics (TOG), 2002.

[3] S. Li, X. Kang, and J. Hu. Image fusion with guided filtering. IEEE Transactions on Image Processing, 2013

[4] C. Tomasi and R. Manduchi.Bilateral filtering for gray and color images.In ICCV, 1998.

[5] S. Paris and F. Durand. A fast approximation of the bilateral filter using a signal processing approach.In ECCV. 2006.